Msc Project report

Msc in Electrical and
Electronics Engineering
(Communication System)

DSP based Adaptive Filter

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August 2002

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by

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Report submitted to the Department of Electronics,
Communications and Electrical Engineering of the University
of Hertfordshire in partial fulfilment of the requirements for the
award of Master of Science

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Abstract

Rapid Digital Signal Processing (DSP) development has contributed to lots of invention in today's technology. DSP are mainly with the digital representation of analogue signals, which is continuous with time signal that had been sampled at regular intervals and then converted into digital form. When a signal is corrupted by noise, filters are used to extract the signals from noise in order to obtain the noise free source.

There are basically two ways of designing a filter, where one is by knowing the exact information of the signal source property, the conventional filter and the other one is the contradiction of the previous statement, where no exact information of the signal source property is known. This type of filter is named adaptive filter. Adaptive filter consists of two distinct parts, which are digital filter and adaptive algorithm. Adaptive filter is used to perform a desire processing and to adjust the coefficient of the filter respectively.

In this report, it is mainly discussing the adaptive algorithm, how does it function. The adaptive filter using Least Mean Square (LMS) adaptive algorithm and FIR digital filter is the main concentration. Then this structure is modeled as software using Visual Basic language. Thus from literature search of adaptive filter, it will then describing the technique of converting concept into a software tool. The performance of LMS algorithm is then being carried out and is analyze.

Acknowledgments.

I would like to take this opportunity to express my gratitude to my project supervisor Prof. Talib Alukaidey for all the help he had supplied throughout the entire process of developing this project. He has been a very supportive supervisor and under his supervision, I managed to learn a lot in various aspects.

Besides that I would also like to thank Mr. Loo Kok Keong who is currently doing PhD programme in Engineering department. His advice and useful criticism help to boost my enthusiasm towards this project.

I would also like to thank my entire friend for being there for me when I need their support. They are so helpful that I didn't imagine there could be such a great friend and helper.

Finally I would like to thank my family for their love and support. There are being so great to me especially when I am in pressured.

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August 2002

Contents

List of Figure

List of Abbreviation

DSP	Digital Signal Processing
FIR	Finite Impulse Response
IIR	Infinite Impulse Response
LMS	Least Mean Square
RLS	Recursive Least Square
MSE	Mean Square Error
VB	Visual Basic
GUI	Graphical User Interface

Chapter 1

Introduction

'Filtering' is a very common task in Digital Signal Processing world. Filtering means a process of extracting a data, which was corrupted by noise. In order to obtain the original noise free source, the corrupted data must undergo a filter. There are basically two ways of designing a filter, where one is by knowing the exact information of the signal source property, the conventional filter and the other one is the contradiction of the previous statement, where no exact information of the signal source property is known.

When filters work in an unknown environment, where identification is impossible, it must be capable of adapting to such situation so that it can perform optimally. Thus adaptive filter can be used to solve this problem. Adaptive filters are capable of obtaining the necessary information without knowing any priori information of the relevant signal characteristics thus enabling the filter to react even there is any changes to the environment.

1.1 General Description of Adaptive Filters

An adaptive filter is a computational device that attempts to model the relationship between two signals in real time in an interactive manner. Adaptive filters are well accepted in communication systems, for echo cancellation and line equalization. An adaptive filter is also suitable for real time control systems for different kinds of applications related to real-time optimisation. Adaptive signal processing is also expanding in other fields such as radar, sonar, seismology, and biomedical electronics.

An adaptive filter could be implemented as an open-loop filter or a closed-loop filter. The algorithm operates in an iterative manner and updates the adjustable parameters with the arrival of new data and current-signal performance feedback parameters. During each iteration, the system will learn more about the characteristics of the input signal. The processor makes adjustments for the current set of parameters based on the latest system performance, i.e. the error signal e(n). The optimum set of values of the adjustable parameters is then approached sequentially. Adaptive filters are often realized as a set of program instructions running on a digital signal processor.

Generally four aspects can define an adaptive filter. First the signals are being processed by the filter x(n). Secondly, the structure that defines how the filter output is computed from its input signal. Thirdly the filter parameters can be interactively changed to alter the filter's in-out relation. Finally, the adaptive algorithm that describes how parameters are adjusted from one time instant to the next.

1.2 Project Aims and Objectives.

The main purpose of doing this project is to understand the concept of adaptive filtering. With this concept, a software tool named 'DSP based Adaptive Filter Software' is created in order to perform comparison of using different parameter of Least Mean Square (LMS) and Recursive Least Square (RLS) adaptive algorithms.

The aims and objective of this project are:

- To introduce a software tool or a software learning kit which can help user to understand more about adaptive filtering.

- To generate a software tool to perform comparison of using different adaptive algorithms for different configuration so that engineer will have clear description which algorithm to use in order to get the best design.

- To enable the engineer or designer to choose the best parameter of adaptive algorithm in order to enhance performance of their design.

- To enhance engineer or designer to do further investigation and research on adaptive filter based system by providing this software tool.

- To increase more system using application of adaptive filter since this software tool can help boost the performance of the systems.

- To minimize the time and cost of providing adaptive filter based system configurations.

- To boost self-development in developing extra knowledge of other field for instance software programming.

- To understand more precisely about theory and application of FIR adaptive filter for different system configurations.

- To develop good skills of managing project by providing a good time management.

1.3 Project Outline

This project is mainly about designing software tool to enable engineers and designer to choose the best adaptive algorithm for FIR adaptive filter in order to get the best performance out from the system configurations. So before they choose which adaptive algorithm to use, instead of using the old way, performing calculation and testing with equipments then monitor result, engineer can use this tool to minimize their work.

In this project, Visual Basic Language is used to create the software. This language is chosen mainly because it can create programs that work with the Windows operating system. It is an event-driven language where it responds to events to execute different sets of instruction. Besides that it is also an object-oriented language, where it provide graphical user interface (GUI).

1.4 Report Outline

The entire project has been divided into several sections such as section for literature search, software design and testing. Thus in this report, it has several chapters where each chapter will discussed the research work that has been done in order to develop this project.

In chapter 1, it is basically an introduction for reader to understand what is this project about. It clearly state that the aims and objectives of the project. It gives a brief idea how does the whole project is developed.

In chapter 2, the fundamental of digital signal processing where the structure of adaptive filtering is being discussed. The theoretical of adaptive filtering explaining how does the conventional filter and adaptive algorithm being combined together to form adaptive filter. Besides that this chapter also include various adaptive configurations and its application.

In chapter 3, it will discuss about the technique of designing the software using Visual Basic language. An overview of Visual Basic and the reason of choosing this programming language are mentioned. Then the implementation of LMS and RLS adaptive algorithm are being discussed.

In chapter 4, the properties of LMS adaptive algorithm are highlighted. Analysis on the LMS algorithm's parameter is discussed in this chapter. Besides that, experiments carried out to performance analysis of LMS algorithm are also highlighted in this chapter.

In chapter 5, it will discuss about the software description. It indicates how to interface with the software and give user a guideline to use it.

In chapter 6, it summarizes the whole project with the achievements obtained from the project research. Future works for this project is also mentioned.

Chapter 2

Adaptive Filter

Adaptive filters are digital filters capable of self-adjustment. These filters can change in accordance to their input signals. An adaptive filter is used in applications that require differing filter characteristics in response to variable signal conditions. An adaptive filter has the ability to update its coefficients. New coefficients are sent to the filter from adaptive algorithm that modifies the coefficients in response to an incoming signal. The digital filter is typically a special type of finite impulse response (FIR) filter, but it can be also an infinite impulse response (IIR) or other type of filter.

2.1 Structure of Adaptive Filter

Adaptive filter consists of two parts, which are a programmable digital filter and an adaptive algorithm. The programmable digital filter is designed to produce a desired output with respect to a sequence of input data. Where else the adaptive algorithm is used to perform adjustment to the tap weights of the filter. Figure 2.1 shows the structure of an adaptive filter.

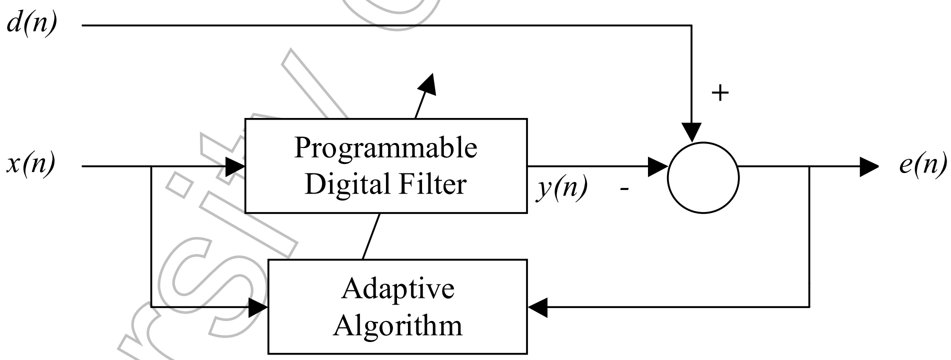


Figure 2.1 Block diagram of adaptive filter

This filter has a reference input signal, x(n),an output signal produced by the programmable digital filter, y(n), a desired response d(n) and error, e(n),which is the difference between desired response and output signal. The adaptive algorithm then adjusts the tap weights of the digital filter in order to minimize the mean square error. Thus from sample to sample, the tap weights of the digital filter will be updated.

2.2 Programmable Digital Filter

There are two types of linear digital filter, finite impulse response (FIR) and infinite impulse response (IIR) filter, which can be used to implement adaptive filters.

2.2.1 Finite Impulse Response (FIR) Filter.

There is basically several FIR realization structures such as transversal structure, linear phase structure, frequency sampling structures and etc. The transversal structure is the most simple structure compare to others. It's simplicity is the main attraction of this structure where it is easy to program and efficient [1,2]. The transversal filter structure or is more known as tapped delay is the most popular FIR structure and is depicted in Figure 2.2

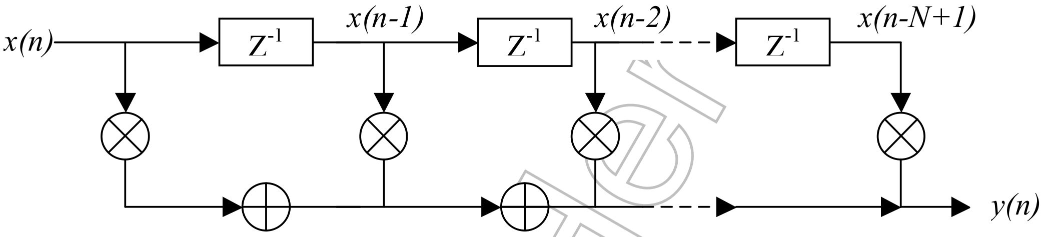


Figure 2.2 Transversal FIR filter

Basically it consists of three elements, which are unit delay element, multiplier and adder [1]. In Figure 2.2, the symbol Z^{-1} represents a delay of one sample where x(n-1) is x(n) delayed by one sample. The number of delay element, shown as N-1 or known as filter order is use to determine the finite duration of the impulse response [1]. The multiplier in the filter is used to multiply the tap input with the respective tap weight (filter coefficient). For instance multiplier connected to the n^{th} tap input x(n-k) produces product of w_k x(n-k) for k = 0,1,2….,N-1.

From the structure in Figure 2.2, the tap-weight vector, *wi(n)* is represented as

$$w(n) = [w0(n), w0(n), \ldots, w0(n)] \qquad (2.1)$$

the tap-input vector, *x(n)*, as

$$x(n) = [x(n), x(n\text{-}1), \ldots, x(n\text{-}N\text{+}1)] \qquad (2.2)$$

The filter output for transversal filter can be expressed as:

$$y(n) = \quad w_k{}^* \; x\,(n\text{-}k) \qquad (2.3)$$

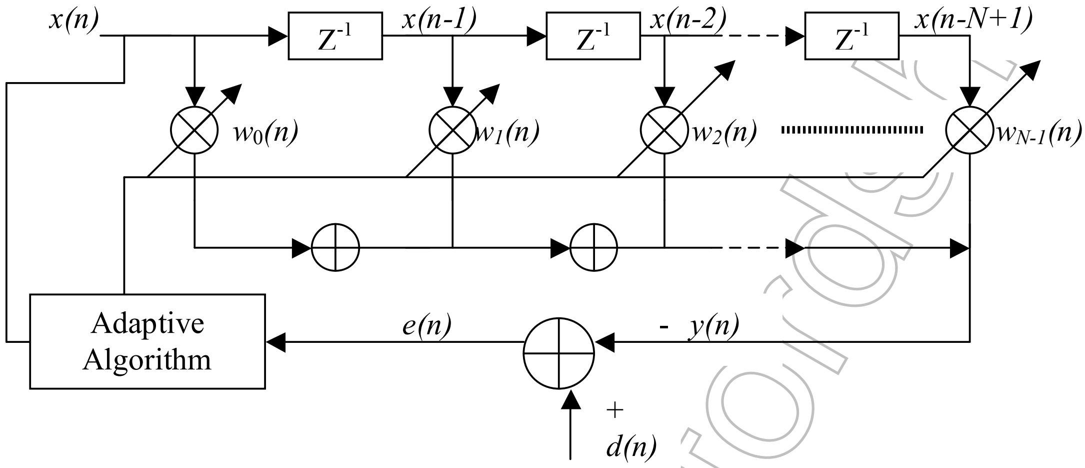


Figure 2.3 Adaptive transversal filter

Figure 2.3 shows the structure of the transversal filter in the implementation of adaptive filter using FIR digital filter. This filter has a single input, *x(n),* and an output, *y(n)*. The output is generated using equation (2.3). Here there is a desired signal, *d(n)*, which is required for adaptation process. For adaptive filter, the tap weights will vary with time, which are controlled by the adaptive algorithm. The tap weights or the coefficient of the FIR filter will vary from sample to sample to minimize the mean square error.

2.2.2 Infinite Impulse Response (IIR) Filter

There are three structures commonly used to implement IIR filter, which are direct form, cascade form and parallel form. The transfer function of an IIR filter can be expressed as

$$\sum_{k=0}^{N-1} a_k(n)x(n-k) + \sum_{k=1}^{M-1} b_k(n)y(n-k) \tag{2.4}$$

The structure releasing this equation is called the direct form and is shown in Figure 2.4

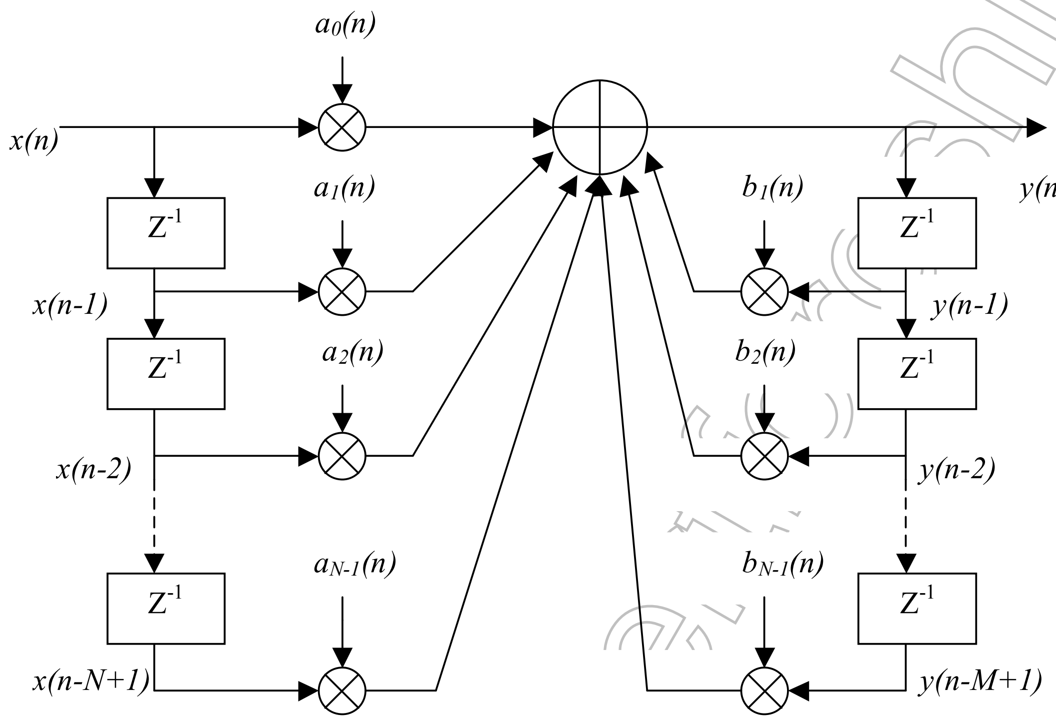


Figure 2.4 Direct form of IIR filter

The coefficient *a* and *b* are the feed forward and feedback tap weight respectively. From equation 2.4, it can be observed that the value of the present filter output sample, *y(n),* is a function of past outputs, *y(n-k)* as well as present and past input samples, *x(n-k).* This structure forms a pole-zero filter design where coefficients a control the zero location and coefficients b control the pole location [3]. The advantage of IIR filter is that it is possible to realize sharp cutoff filter characteristic with the inclusion of poles and zeros. But one major problem with adaptive IIR filter design is the possible instability of the filter since poles could be outside the stable region [5].

2.2.3 Comparison of Finite Impulse Response Filter and Infinite Impulse Response Filter.

In adaptive filter applications, Finite Impulse Response (FIR) filter is more commonly used compare to Infinite Impulse Response (IIR) filter. This is mainly because the design structure and the characteristics of FIR filter.

Finite Impulse Response (FIR) filter has a finite memory and have excellent linear phase characteristics. There is no phase distortion being introduced into the signal by the FIR filter where else Infinite Impulse Response (IIR) filter produce non-linear phase distortion [2]. Hence FIR filter is more reliable to be implement compare to IIR filter.

FIR filter design is always stable since it only involves zeros and reliazed non-recursively but IIR filter is not always stable due to its design involves both zeros and poles. IIR filter requires fewer coefficients, which then contribute to sharp cutoff but the drawback is that it will become unstable. When fewer coefficients are required in filter design, it means processing time and storage will decrease.

2.3 Adaptive Algorithm

The most important part of an adaptive filter is the adaptive algorithms. It has very unique features where it will vary the tap weights filter in order to minimize the mean square error (MSE) according to some criterion. The most common adaptive algorithm for adaptive filter application is the Least Mean Square (LMS) and Recursive Least Square (RLS). Both of these algorithms have their own advantages over each other where it depends on the application.

2.3.1 Least Mean Square (LMS) Adaptive Algorithm

Widrow and his coworkers develop LMS algorithm in 1975. This algorithm is widely used in adaptive signal processing such as noise cancellation and prediction. In real time LMS is easy to implement where the process of updating the filter tap weights (coefficient) are based on steepest descent algorithm [1]. The coefficients are updated from sample to sample using the following equation:

$$w(n+1) = w(n) + \mu e(n)x(n) \qquad (2.5)$$

where $w(n)$ is the tap weights of the digital filter,
$e(n)$ is the error signal,
$x(n)$ is the tap inputs,
μ is the step size.

The resultant new weight based on equation (2.5) is only estimation but this will improve as the algorithm learns the characteristics of the signals. The step size, μ, is the parameter, which control the stability and the rate of convergence [1,2]. Thus a proper value of μ must be assigned in order to ensure convergence. The condition for convergence of the LMS algorithm in the mean square is

$$0 < \mu < (2/\text{tap input power}) \qquad (2.6)$$

where the tap input power is the sum of the mean square values of tap inputs $u(n)$, $u(n-1), \ldots, u(n-N+1)$ [1]. One draw back from LMS algorithm is that there is only one adjustable parameter, which is μ that affects convergence rate.

2.3.2 Recursive Least Square (RLS) Adaptive Algorithm

RLS adaptive algorithm uses least square method to estimate correlation directly from the input data. This method allowed convergence rate to decrease and hence the computation for the process of obtaining optimum weight is faster compared to LMS algorithm. The tap weights are updated using

$$w(n) = w(n-1) + ke(n) \tag{2.7}$$

where k is the Kalman gain and
$e(n)$ is the error signal

Basically RLS algorithm implemented in transversal FIR filter is similar to the LMS algorithm in the term of obtaining the digital filter, $y(n)$. The only different is in the adaptation process where RLS uses least square method. Here the Kalman gain vector is based on input-data auto-correlation results, the input data and a factor called the forgetting factor. The forgetting factor can be in the range between zero and one. The

2.4 Adaptive Filtering Application

The uniqueness of adaptive filter where it can operate in an unknown environment makes it so powerful and suitable to be applied into a lot of Digital Signal Processing (DSP) fields such as communications, radar, sonar, etc [1]. For adaptive filter, there are at least four system configurations that can be set up which are Adaptive Identification System, Adaptive Inverse System, Adaptive Linear Prediction and Adaptive Noise Cancellation.

2.4.1 Adaptive Identification System Configuration

Adaptive Identification System Configuration can be applied as Modem Echo Cancellation, Layered Earth Modelling, etc. The architecture of this system configuration is illustrated in Figure 2.5.

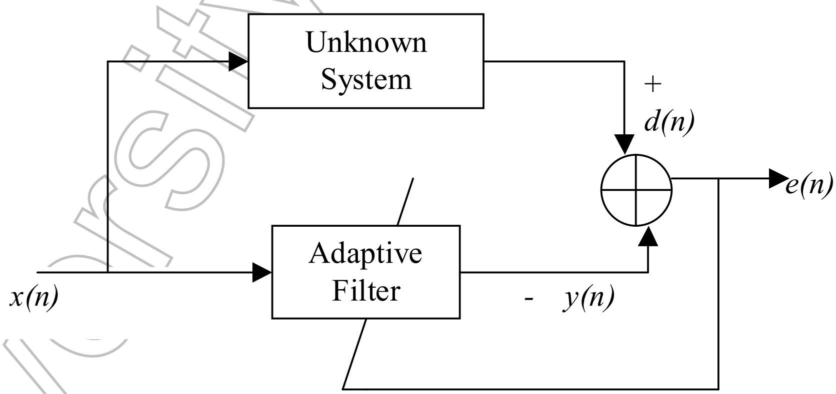


Figure 2.5 Adaptive System Identification Configurations

As shown in Figure 2.5, this configuration has same input applied to adaptive filter and unknown system. The error signal, *s(n),* is the difference between the output of the adaptive filter,y(n), and the output of the unknown system, *d(n)*.Thus if the adaptive filter successfully minimizing the error to zero, the transfer function of the unknown system must be identical to the transfer function of adaptive filter. The weight will then remain stable and unchanged as long as the transfer function of the unknown system does not change and then it can be said that the system is identified.

2.4.2 Adaptive Inverse System Configuration

The applications of adaptive Inverse System Configuration are Channel Equalization and Adaptive Equalization. The structure of this configuration is shown in Figure 2.6.

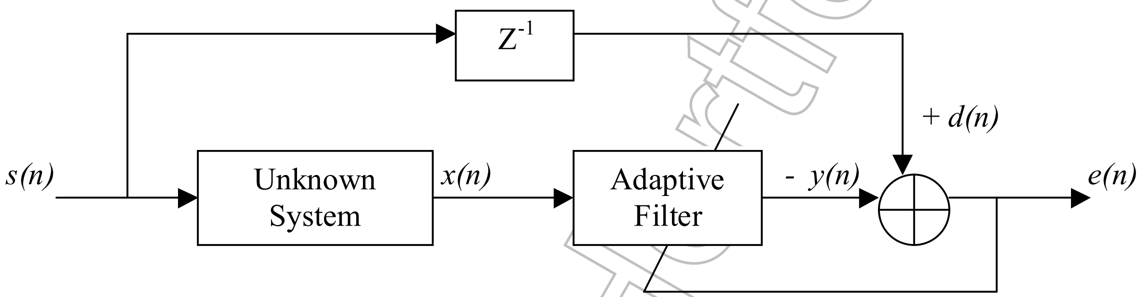


Figure 2.6 Adaptive Inverse System Configurations

Input *s(n)* is applied to the unknown system and then to the adaptive filter where it then generate an output, *y(n*). Input also applied to a delayed element to obtain a desired signal, *d(n*). The delay element is used to ensure that the problem is casual and is solvable in real time system. Similar to the Identification System Configuration, the transfer function of the adaptive filter must be same with the transfer function of the inverse unknown system.

2.4.3 Adaptive Noise Cancellation Configuration

Another configuration of adaptive filter is the adaptive noise cancellation configuration. This configuration can be applied as noise canceling, beam forming and ECG noise control. Figure 2.7 shows the structure of the adaptive noise cancellation configuration.

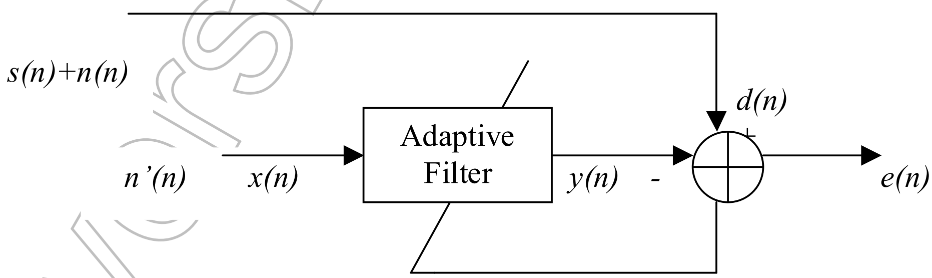


Figure 2.7 Adaptive Noise Cancellation Configurations

A correlated noise reference signal, *n'(n)* is applied to the adaptive filter and the output, *y(n),* is compared with the desired signal, *d(n)*. Here the desired signal consists of a signal, *s(n),* corrupted with a noise signal, *n(n)*. Hence whenever the adaptation takes place, it will vary the filter weight, which completely models the noise signal. Thus it can be expected that the error signal is equal to the input signal [*e(n) = s(n)]* when the filter's weights stop varying.

2.4.4 Adaptive Linear Prediction Configuration.

Finally the last configuration is the adaptive linear prediction. This configuration is applied to linear prediction coding, signal detection, adaptive CDMA receiver, etc. The structure of this configuration is shown in Figure 2.8.

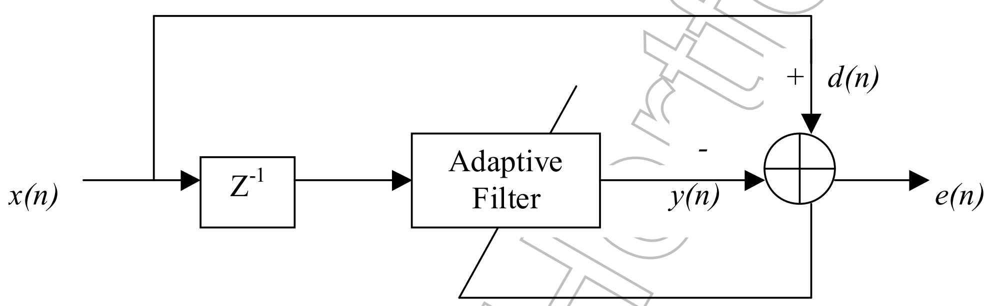


Figure 2.8 Adaptive Linear Prediction Configurations

For this type of configuration, when the error signal is adapted to zero then the adaptive filter will predict the future element of the input signal, *x(n),* based on previous observation.

Chapter 3

Implementation of Adaptive Filter Algorithms using Visual Basic

In previous chapter, the structures and various configurations of adaptive filters had been discussed. Now in this chapter, the adaptive filter algorithms will be discussed in more detail, where it is the main purpose of the project. As had been discussed in Chapter 2, basically there are two common adaptive filter algorithms, the Least Mean Square (LMS) and the Recursive Least Square (RLS) algorithms. Here, the main focus will be the Least Mean Square (LMS) algorithm. Thus it is wise to understand how does this algorithm actually being designed and work using Visual Basic Language.

3.1 Introduction of Visual Basic

Visual Basic language is a programming language, which works well with the Windows operating system. Thus it can be said that this language is used to create Windows-based applications. This language is very popular with the ability of creating graphical user interface (GUI) program. Typical drag-and-drop techniques are used to design the software.

A Visual Basic application is make up by small components. The most common components are form, control and procedures. Forms are the windows upon which used to build user interface. Controls are interface tools such as label, text boxes and command button where each of it have their own function. Label is used to display information to the user, text boxes is used to gather information and command button is used to respond to user actions. Procedures are small routines that callable from anywhere in application. These routines will perform the routines function whenever it is called.

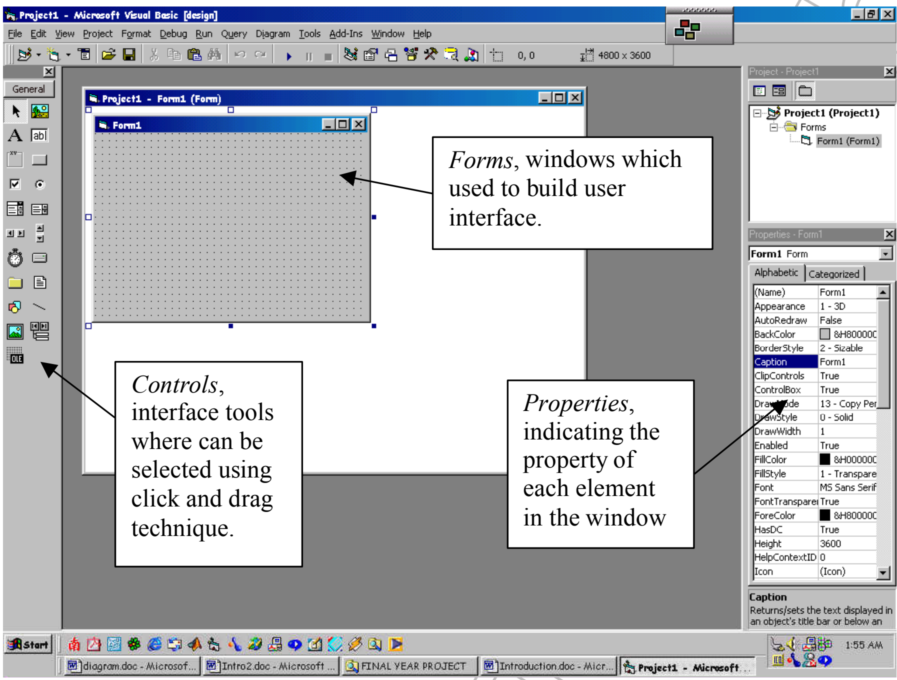


Figure 3.1 Visual Basic's design environment

Events is the most important concept of Visual Basic programming where it response to user interaction with the keyboard or mouse. It can be said that events are messages to the application. An event procedure is a segment of code that is executed when a particular event occurs to a particular object. Thus the event procedure is corresponding to events.

In this project the main reason of using Visual Basic 6.0 as a development tools is because it has graphical user interface (GUI). User of this software, can easily applying inputs to the program and the result is then displayed either using graphical method or text method.

3.2 Designing Adaptive Filter Algorithm

Adaptive filter using LMS algorithm is designed based on the mathematical flow of obtaining LMS weight's update equation.

3.2.1 Implementation of Least Mean Square Algorithm

As mentioned in section 2.3.1, LMS is based on the steepest descent algorithm where the weight is updated from sample to sample in order to minimize the mean square error (MSE). The computational procedure to design the LMS algorithm using Visual Basic is based on the LMS computation model illustrate in Figure 3.2.

The whole LMS computation model can be broken down to several stages as shown in Figure 3.2. It is wise to understand how does each block of the flowchart function to come out with a process of updating the filter's weight.

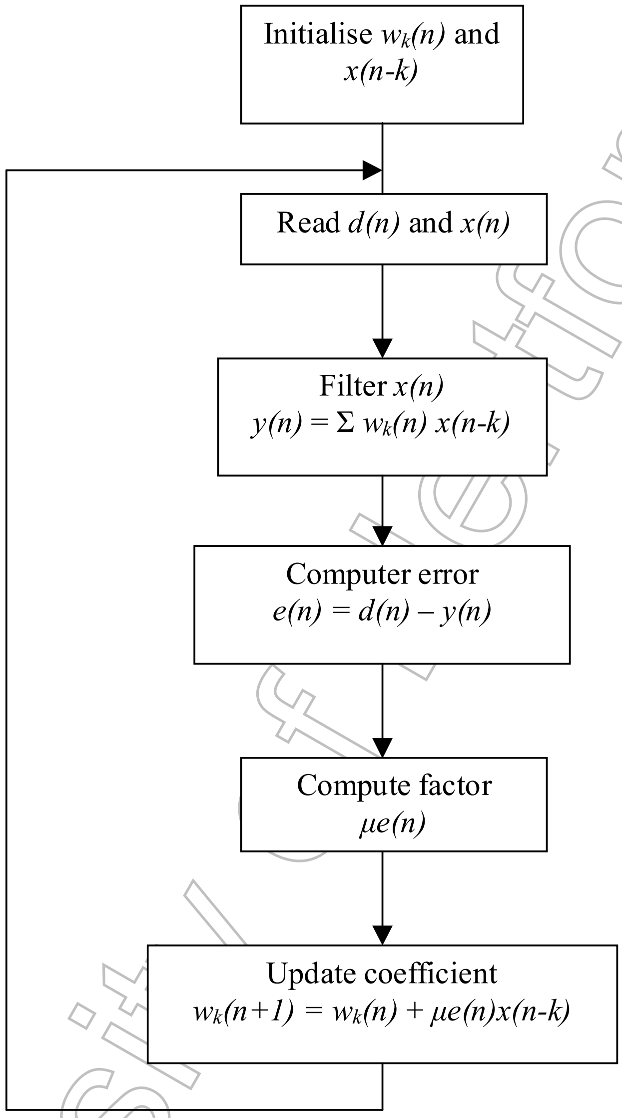


Figure 3.2 Flowchart for the LMS adaptive filter

The stages to implement LMS adaptive filter are:

Stage 1: Initialize $w_k(n)$ and $x(n-k)$

This stage, the filter's weight, $w_k(n)$ and the input data after each delay ,$x(n-k)$, is initialized. Thus for instance the input signal is

$$x(n) = \{0,4,3,2,1,4,\ldots\} \qquad \text{for } t = \{0,1,2,3,\ldots\} \tag{3.1}$$

Then the input signal after one delay will be shifted to the right by one space where it become,

$$x(n-1) = \{0,0,4,3,2,1,4,\ldots\} \qquad \text{for } t = \{0,1,2,3,\ldots\} \tag{3.2}$$

Figure 3.3 illustrates equation 3.1 and 3.2 in discrete input signal form for better understanding.

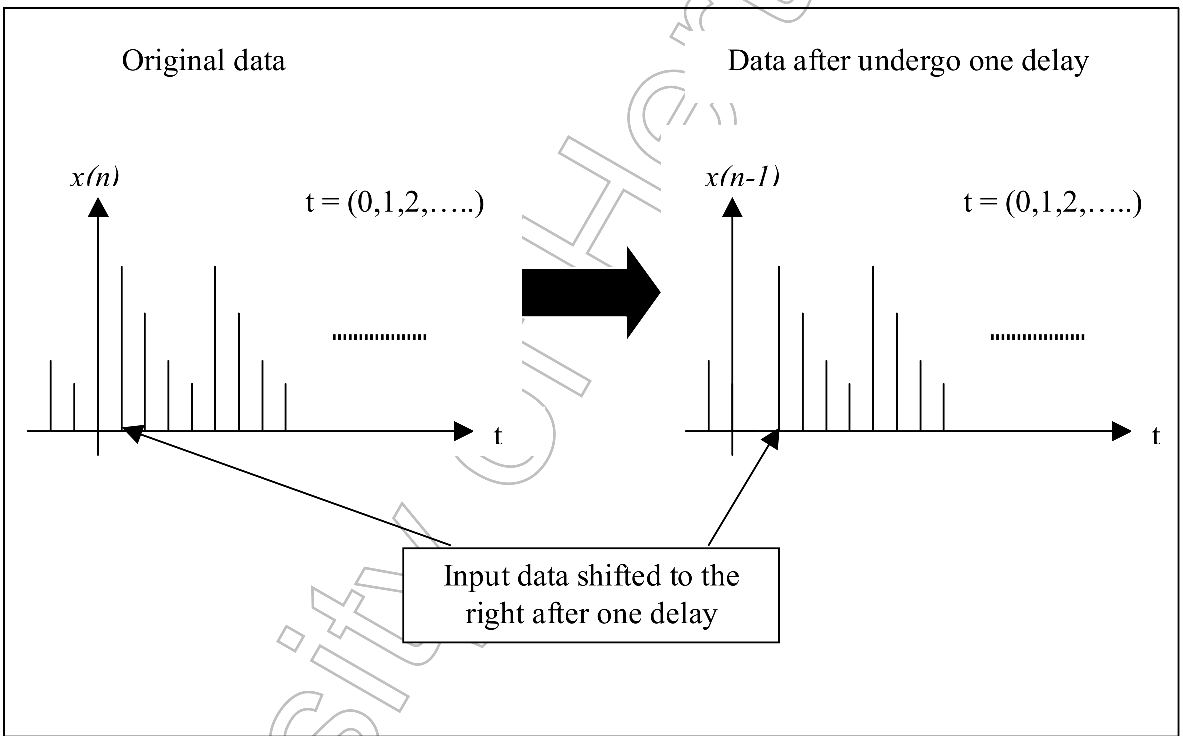


Figure 3.3: (a) Discrete signal of input data, (b) Discrete signal of input signal after one delay

Here each weight $w_k(n)$, where $n = 0,1,\ldots\ldots,N-1$ is set to zero. Filter length, N,

Stage 2: Read *d(n)* and *x(n)*
Desired reference signal, *d(n)* and the input signal, *x(n)*

Stage 3: Filter *x(n)*
In this stage, the adaptive filter output is obtained using this equation:

$$y(n) = \sum_{k=0}^{N-1} w_k(n) * x\,(n-k) \tag{3.3}$$

Equation 3.3 shows that the adaptive filter output is basically the convolution of tap weight, w_k *(n)* and input signal, *x(n)*.Thus the output, *y(n),* is the summation of the multiplication of each tap input with its respective tap weight. The filter length, N is the number of filters weight and k is the filter taps. Figure 3.4 illustrates the process of convolution between the tap weight and the tap input.

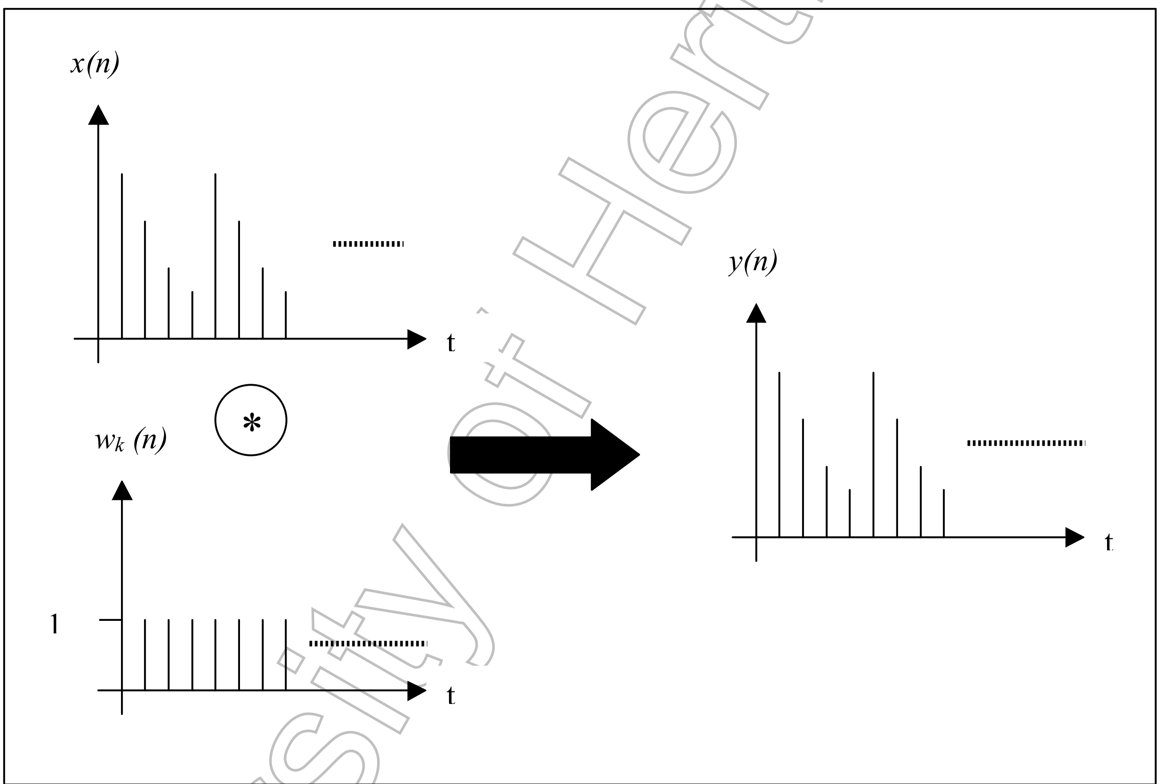


Figure 3.4 The convolution *y(n)* of *x(n)* and w_k *(n)*

Stage 4: Compute error
Error is the difference between the desired input signals with the output signal of the adaptive filter. It can be obtained using

$$e(n) = d(n) - y(n) \tag{3.4}$$

Stage 5: Compute factor
The step size, μ play an important role to determine the convergence rate of Least Mean Square method. This stage is to compute factor of the set size with the error obtained from previous stage. This is for easier testing and upgrading purposes in the future.

Stage 6: Update coefficient
This is the final stage of LMS computation model where the coefficient of the filter tap weights are updated using

$$w_k(n+1) = w_k(n) + \mu e(n)x(n-k) \tag{3.5}$$

Thus each tap weights of the respective tap inputs will be updated from sample to sample in order to minimize the mean square error.

3.2.2 Implementation of Recursive Least Square Algorithm

The major advantages of LMS algorithm lays in its computational simplicity but this lead to slow convergence, especially when the eigenvalues of the autocorrelation matrix have a large spread. Hence in order to have faster convergence, thus RLS algorithm is used.
The computational procedure for Recursive Least Square (RLS) algorithm is more complex compared to the LMS algorithm. It uses least square method, where it deal directly with the data sequence $x(n)$ and obtain estimates of correlations from the data.

Now lets have a look of how RLS algorithm computation procedure to obtain new filter coefficient is done. The important parameters of RLS algorithms: N is the number of filter weights, s = 1/forgetting factor, k is the Kalman gain N-by-1 vector, $x = [x(n), x(n-1), \ldots x(n-N+1)]$ is the input samples and $w = [w_0, w_1, \ldots w_{N-1}]$ is the filter weights, where each weight is set to 0.

Stage 1: Initialize $w_k(n-k)$ and $x(n)$
The filter's tap weight and the tap inputs to the respective tap weights are obtained.

Stage 2: Read $d(n)$ and $x(n)$
Desired reference signal, $d(n)$ and the input signal, $x(n)$ are obtained

Stage 3: Filter *x(n)*

In this stage, the adaptive filter output is obtained using this equation:

$$y(n) = \sum_{k=0}^{N-1} w_k(n-k)x(n) \tag{3.5}$$

It can be observed that the output of the adaptive filter at time n based on use of the filter coefficients at time *n-1*.

Stage 4: Compute error

Error is the difference between the desired input signals with the output signal of the adaptive filter. It can be obtained using

$$e(n) = d(n) - y(n) \tag{3.6}$$

Stage 5: Compute Kalman gain vector, *k*

The Kalman gain vector can be obtained using:

$$k = \frac{s * z(n-1).x}{1 + x.[s * z(n-1).x]} \tag{3.7}$$

Stage 6: Update the autocorrelation matrix

The autocorrelation matrix now is updated using:

$$z(n) = s*z(n-1) - k.[s*z(n-1).x]^T \tag{3.8}$$

Stage 7: Update the tap weights

The tap weight of the filter are updated

$$w(n) = w(n-1) + ke(n) \tag{3.9}$$

Chapter 4

Property and Performance of LMS Algorithm

4.1 Properties of LMS Algorithm

In this chapter, the basic properties of LMS algorithm will be discussed. These properties will then lead to the measurement of performance of LMS algorithm. Here it will focus on LMS algorithm performance in respect to its convergence properties, its stability, and its minimum mean square error, its robustness and how filter length affects its performance. Then the simulation and results obtained from the software will be discussed in order to get a better idea how does the LMS properties affect the performance of LMS algorithm.

4.1.1 Convergence Rate

Convergence rate is the rates of determining the initial tap weight of the filter converges to the optimum tap weight. The convergence rates of the LMS algorithm can be investigate by determining how the mean value of initial tap weight converges to the optimum tap weight. In order to obtain convergence, two requirements must be satisfied. First, the filter coefficients approach the optimum weight as $n \to \infty$ (the number of iterations approaches infinity). Second, the average mean-square error approaches a constant value as $n \to \infty$.

Both of these requirements can be satisfies if a proper step size is used, which it has the following condition:

$$0 < \mu < \frac{2}{total\_input\_power} \tag{4.1}$$

where the total input power is the sum of the mean-square values of the tap inputs *u(n), u(n-1),…..,u(n-N+1)*. Hence this show that the step size play an important role in LMS algorithm that affects the convergence rate of this algorithm. A proper step size is needed to avoid misadjustment of Mean Square Error (MSE).

4.1.2 Mean Square Error (MSE)

Mean Square Error (MSE) is the parameter, which used to analyse how well is the adaptive system being accurately modelled. It is the metric of measuring the performance of the adaptation for the filter's weight to converge to the solution for the system. Normally, the final value of mean square error, *J(n)* produced by the LMS algorithm is constant at the end of the convergence. The mean square error, *J(n)* can be obtained by:

$$J(n) = \Sigma \mid e(n)^2 \mid \tag{4.2}$$

Thus if this is satisfied, this algorithm is said to be convergent in the mean square. The curve obtained by plotting the mean square error with respect of the number of iteration, n is known as learning curve. The learning curve of LMS algorithm consists of a sum of errors, each of which corresponds to the number of tap weights.

An adaptive system is said to be accurately modelled has small value of minimum MSE where else a large minimum MSE that the system is not accurately modelled.

4.1.3 Filter Length

The filter length indicates the accuracy of a system, which can be modelled by the adaptive system. It affects the convergence rate, the stability of the system and the minimum mean square error.

Misadjustment, $\mathcal{M}$ is defined as the ratio of the steady state value of the excess mean-square error to the minimum mean square error. It is used to measure how close the LMS algorithm is to optimality in the mean square error sense. Therefore the adaptive filtering system is accurately designed if the *misadjustment*, $\mathcal{M}$ is small. The computation time of LMS algorithm is inversely proportional to the *misadjustment*, $\mathcal{M}$. The filter length will affect the convergence rate by varying the computation time. When the filter length of a system is increased, automatically the computation time will increase. Hence as filter length increased, the *misadjusment* will decrease and this lead to faster convergence rate.

For stability, an increase in filter length may add additional poles or zeros that may be smaller than those that already exist. So in order to maintain stability, the maximum convergence rate has to be decreased. When a system has too many poles and zeros for system modelling, it will have potential to converge to zero. However this will increase the calculation, which will then affect the maximum convergence rate.

4.1.4 Stability

Stability of an adaptive system is a very important to determine the performance of an adaptive system. In real world it is difficult to obtain a completely stable adaptive system but a reliable system can be obtained when certain LMS algorithm parameter is adjusted. For instance the step size, μ can affect the stability of the system. With large step size, μ, it obtains faster convergence time but the stability of the system will decrease. Conversely when smaller step size, μ is used, the stability of the system will increased One aspect that have to be take into account is that larger step size, μ, improved the convergent rate hence lead to simpler computational complexity. Thus a system has to be designed with respect to all this aspect.

4.1.5 Computational Complexity

Computational complexity is another aspect to be considered when an adaptive system is being modelled. In real time when a system is being implemented, hardware limitations can bring a huge problem to the performance of a system. When a system is designed using a much complex algorithm, it requires much greater hardware resources than a simpler algorithm. This is the reason LMS algorithm is much more preferred compared to RLS algorithm.

4.1.6 Robustness

One of the interesting aspects of the LMS solution is its robustness. Robustness of a system is directly proportional to the stability of a system. It is used to measure how well does the system resisting noises. For LMS, no matter what the initial condition for the weights, the solution always converges to basically the same value. This robustness is rather important for real- world problems, where noise is universal. Robustness of a system can also be affected by the choice of LMS algorithm parameter.

4.2 Simulation and Result.

In this section, two experiments had been carried out in order to see how do the step size and the filter's length affect the performance of LMS algorithm. The simulation and the result are displayed as learning curve of MSE and tap weight. The simulation will clarify the properties of LMS algorithm, which has been discussed in section 4.1.

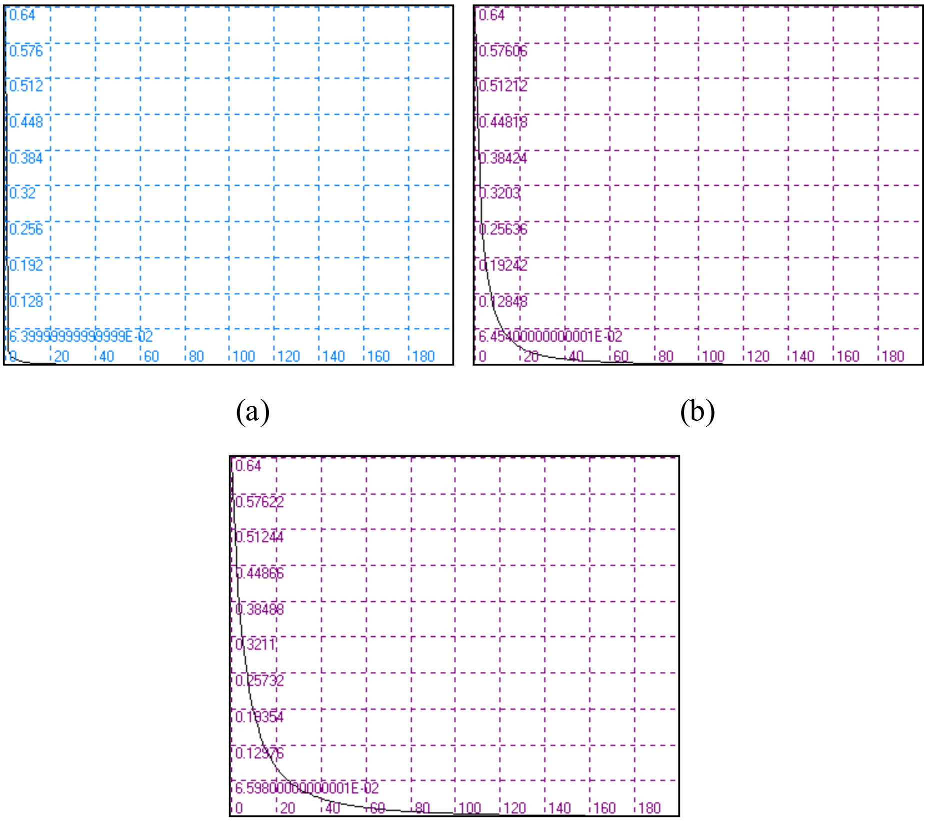
4.2.1 Experiment 1

The first experiment is to observe how the step size, μ affect the convergence rate. So a set of parameter is used to perform this experiment. Here the LMS algorithm parameter is set to be:

Filter length, N = 2
Initial tap weight, $w_0 = 0$
No of iteration = 200
Optimum weight = 0.8

Using the above parameter, and applied to the software, the results of varying the step size are obtained. This software provides learning curves of the system where performance of the system can be analyse from this curves. Figure 4.1 shows the Mean Square Error performance of the system while Figure 4.3 shows performance of the adaptation of initial tap weight to the optimum tap weight.

The graph parameter of Figure 4.1:
y-axes → Mean Square Error, MSE
x-axes → No of iteration, n



(a) (b)

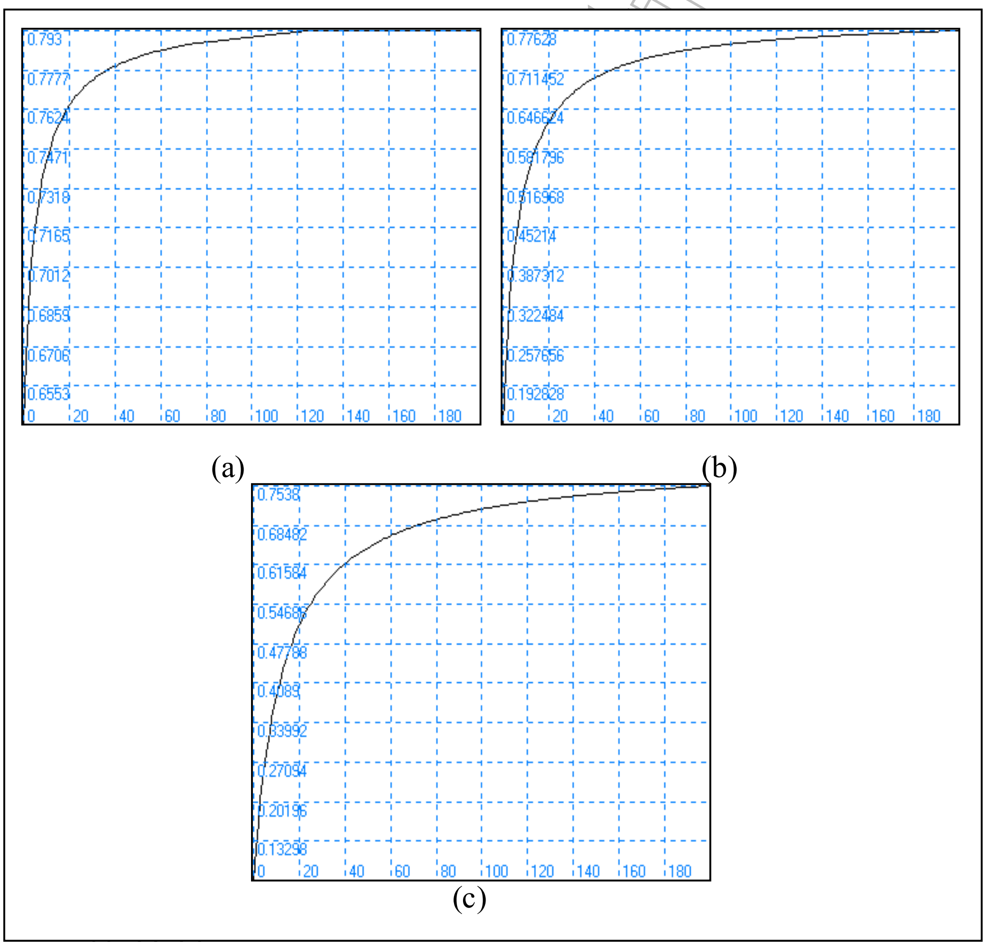
(c)

Figure 4.1 MSE performance using step size of (a) 0.5, (b) 0.1 and (c) 0.05

No	Step size	Tap weight	No of iteration
a	0.5	0.7930	120
b	0.1	0.7763	185
c	0.05	0.7538	200

Table 4.1 Results obtained when using different step size for tap weight analysis

The graph parameter of Figure 4.2:
y-axes → Tap Weight
x-axes → No of iteration, n



(a) (b) (c)

Figure 4.2 Tap weight performance using step size of (a) 0.5, (b) 0.1, (c) 0.05

As can be observed in the simulation shown in Figure 4.1, the step size of 0.5 can obtain the fastest convergence rate compare to the others. Hence this prove that step size do affect the convergence rate. As has been discussed in section 4.1 the step size should

meet the condition in equation 4.1 in order to successfully converge to the optimum weight.

One should remember, all the graphs shown in Figure 4.1 are learning curve of measuring Mean Square Error (MSE). So from the beginning the Mean Square Error (MSE) is large. As more iteration goes on, the MSE started to drop and then converge to constant state. This curves proved that the MSE do decay exponentially as more iterations is perform.

Figure 4.2 shows the learning curve of tap weight performance. As the initial tap weight of all filters are set to zero, thus the tap weight of the filter will approach optimum weight as iteration increased. Note that the step size of 0.5 is the fastest. The optimum weight for this experiment is 0.8 and Figure 4.2 shows that the LMS algorithm can successfully converge to 0.793 and become constant at iteration reached approximately 120 for step size of 0.5. Referring to Figure 4.2, all the tap weight doesn't converge to the optimum weight but it becomes constant at certain value, which is very near to the optimum weight.

Hence this concludes that step size of 0.5 is the best step size to use with the LMS parameter in experiment 1. This is because the average mean square error becomes constant in the shortest period. The robustness of the system is good since the difference between the optimum weight and the converged tap weight is the smallest. Besides that the time taken for the LMS algorithm to reach optimum weight is also the shortest.

This experiment proved that as the step size parameter is increased, the rate of convergence of the LMS algorithm is correspondingly increased. A reduction in the step size parameter also has the effect of reducing the variation in the experimentally computed learning curve.

4.2.2`Experiment 2.

The second experiment is to observe how the filter length, N affect the convergence rate. So a set of parameter is used to perform this experiment. Here the LMS algorithm parameter is set to be:

Step size, $\mu = 0.1$
Initial tap weight, $w_0 = 0$
No of iteration = 200
Optimum weight = 0.8

Using the above parameter, and applied to the software, the results of varying the filter length are obtained. This software provides learning curves of the system where performance of the system can be analyse from this curves. Figure 4.3 shows the Mean Square Error performance of the system while Figure 4.4 shows performance of the adaptation of initial tap weight to the optimum tap weight.

The simulation results shown in Figure 4.3 shows that as filter length increased, the MSE decay to constants state in faster manner. So these clarify the statement made in Section 4.3 where as filter length increase, the convergence rate become faster.

As can be observed from Figure 4.3, the MSE reach constant state approximately 10 iterations for system with filter length of 10. While for system with filter length of 2, the MSE reach constant state at approximately 70 iterations. In real world these bring a huge effects to its computation complexity. With lesser computation, definitely the hardware to implement this system will be easier.

The graph parameter of Figure 4.3:
y-axes → Mean Square Error, MSE
x-axes → No of iteration, n

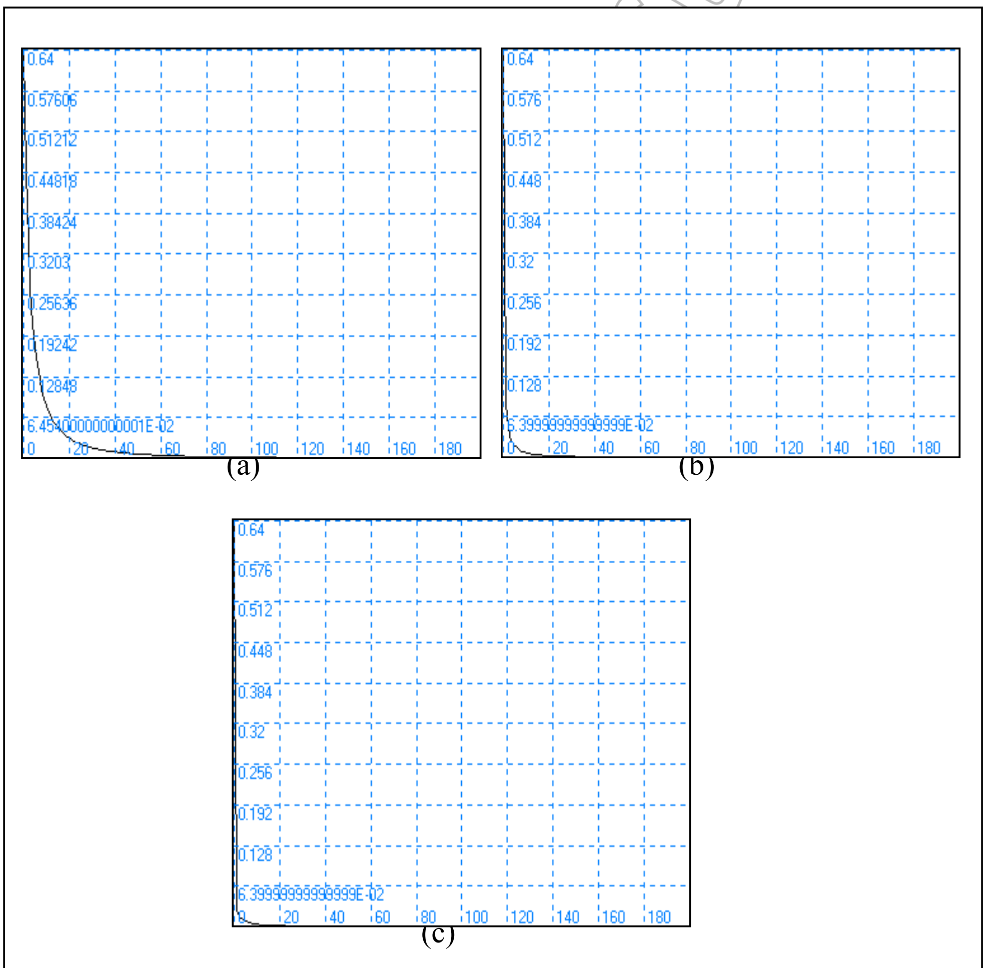


Figure 4.3 MSE performance using filter length of (a) 2, (b) 8 and (c) 10

No	Filter Length, N	Tap weight	No of iteration
a	2	0.7763	185
b	8	0.7929	150
c	10	0.7930	120

Table 4.2 Results obtained when using different filter length for tap weight analysis

The graph parameter of Figure 4.4:
y-axes → Tap Weight
x-axes → No of iteration, n

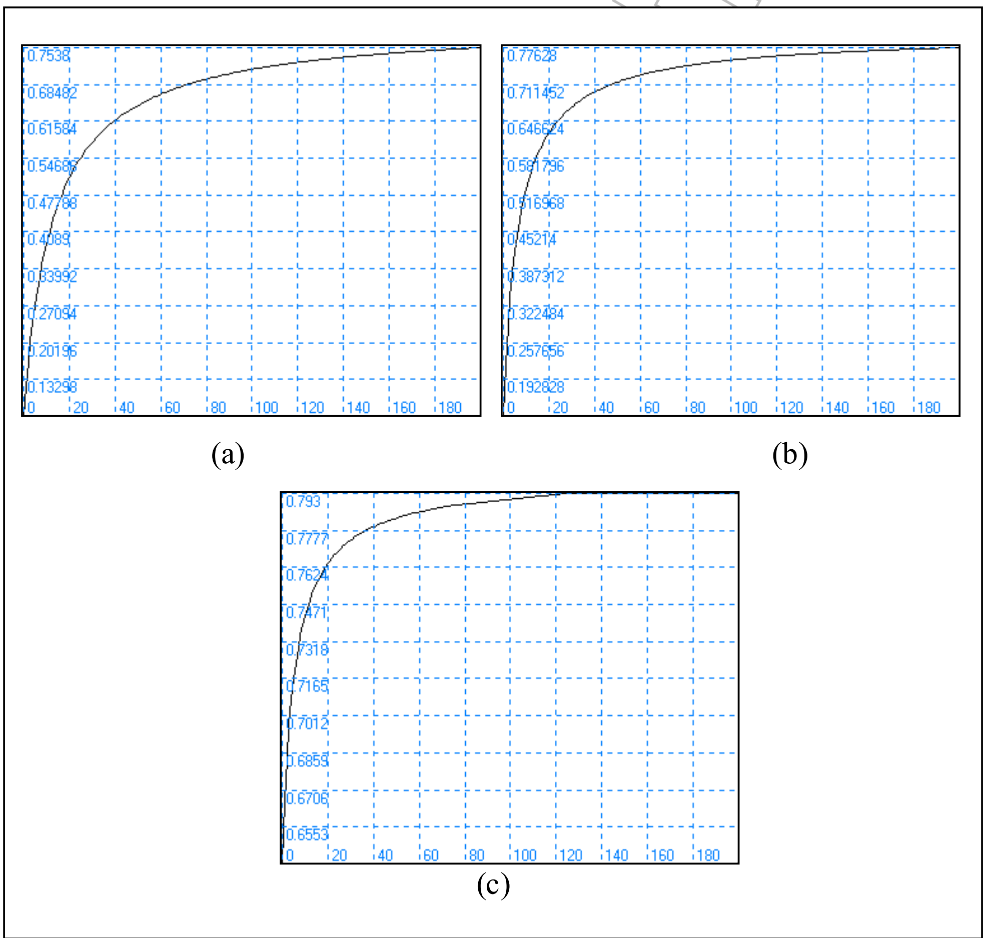


Figure 4.4 Tap weight performance using filter length of (a) 2, (b) 8, (c) 10

As for the performance of tap weight, a system with a larger filter length will adapt to the optimum weight in lesser convergent time. Besides that it also converges to the optimum

weight, where it is quite near to the optimum value. One can refer to Figure 4.4 to have a better description of how the filter length affects the performance of the LMS algorithm.

This experiment proved that as the filter length parameter is increased, the rate of convergence of the LMS algorithm is correspondingly increased. A reduction in the filter length parameter also has the effect of reducing the variation in the experimentally computed learning curve.

4.3 Summary

In this chapter the properties of Least Mean Square (LMS) algorithm has been discussed. Each LMS properties have different affects to the performance of the system. Normally in order to investigate the performance of the system using LMS algorithm, learning curves is used. Learning curves can be used to view the performance of LMS algorithm for both Mean Square Error (MSE) versus no of iteration and Tap weight versus no of iteration.

From experiment 1 and 2, it concluded that in order to successfully build an adaptive system, the LMS algorithm parameter have to be taken into account. The step size and the filter length of the algorithm play a huge role here. This is because the step size and the filter length will determine how well does the system performs. A large step size and within the range in equation 4.1 will give produce a system with small mean square error, a shorter convergence time and provide better robustness of a system. The stability of the system will decrease as large step size is being implemented in the system.

Filter length on the other hand has the same affect to a model system. When a large filter length is used to model an adaptive system, the MSE is small and the convergence time will become lesser but this will lead to more complex computational. As larger filter length is used, this mean that a much more complex computational is required and then much more complex hardware is required to model the system.

Thus in order to have a modelled a good system, the step size and filter must be carefully chosen so that the stability and the computational complexity is taken into account.

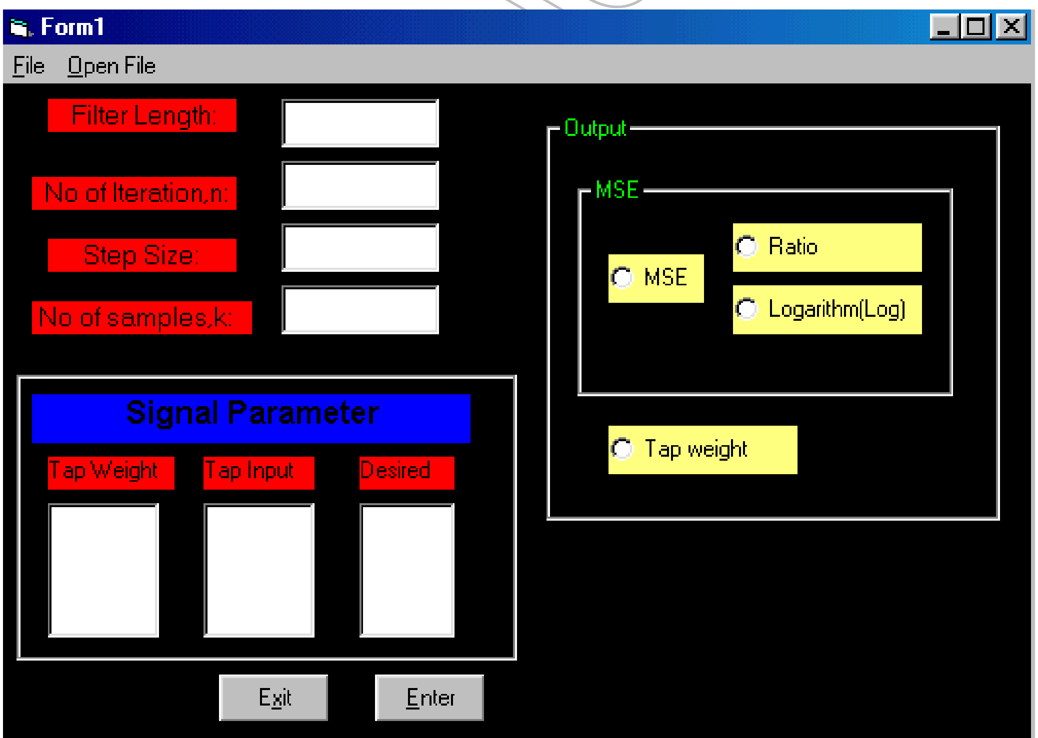
Chapter 5

Software Description

This chapter will give a clear description of using this software. As mentioned in Chapter 3, this software is programmed using Visual Basic language. Thus it will create an atmosphere where user will easily get familiar within a short period. The concept of using this software is easy to understand and user friendly. This chapter gives user an opportunity to understand how to interface with the software in order to view the result of the simulation.

5.1 Overview of Software

Figure 5.1 illustrates the layout of the software. As can be seen, there are few parameters where user can set in.



igure 5.1 Adaptive based Software GUI

5.1.2 Flow of Software

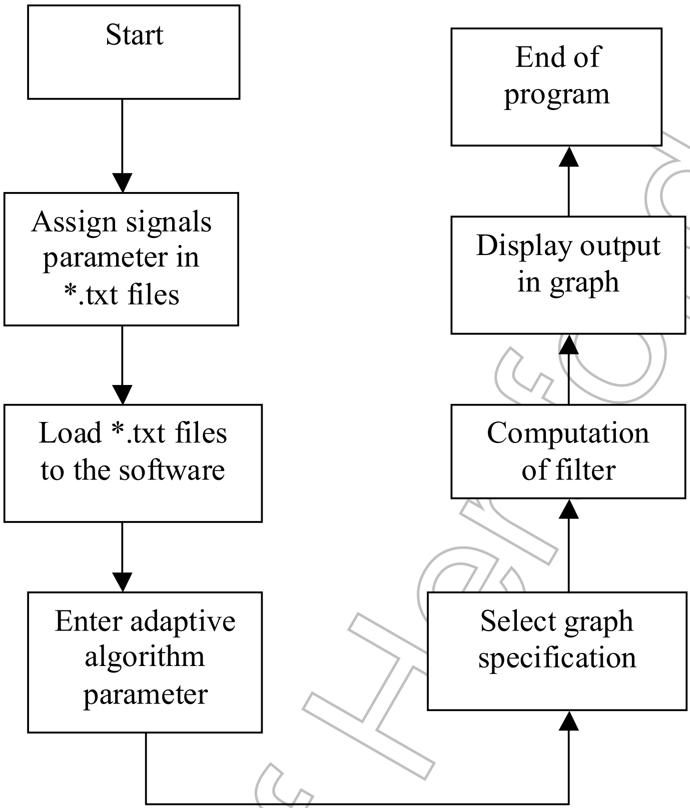


Figure 5.2 Flowchart of Software

Figure 5.2 illustrate the flow of software in a flowchart manner. Basically this is how the software being program to run :

Stage 1: Assign signals parameter in *.txt files
This stage, user have to put all the information of the signal's in *.txt files. For instance tap weight, user have to assign each tap weight in vertical manner in *.txt files because the program will read the data from *.txt files in vertical manner.

Stage 2: Load*.txt files to the software
From *.txt files user can load the information of the respective signals to the corresponding destination. After the information of the signal is loaded into the program then this is the value where the program will use to perform simulation.

Stage 3: Enter adaptive algorithm parameter
User then have to set the parameter of the adaptive algorithm, the step size, filter length, etc.

Stage 4: Select graph specification
User have to select which graph specification he want to view in order to investigate the performance of the adaptive filter. For instance choose between Mean Square Error in ratio form or in logarithm form.

Stage 5: Computation of filter
After all parameters of the adaptive system is being defined then by clicking 'Enter' (refer to 5.2.4) the program will start the computation of filter.

Stage 6: Display output in graph
After the computation of filter is successfully done, then the graph showing the performance of adaptive filter will be displayed.

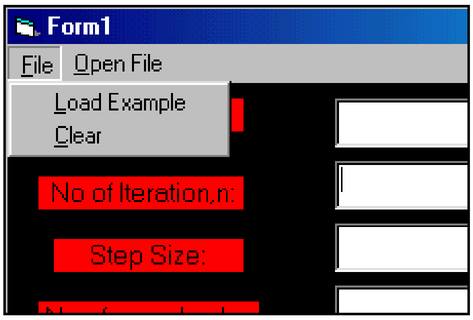
5.2 User's Manual

In this section, the method to interface with the software is being interfaced by the user. All the process being discussed in Section 5.1.2 will be implement in this section. User will then have a brief description of using the software then.

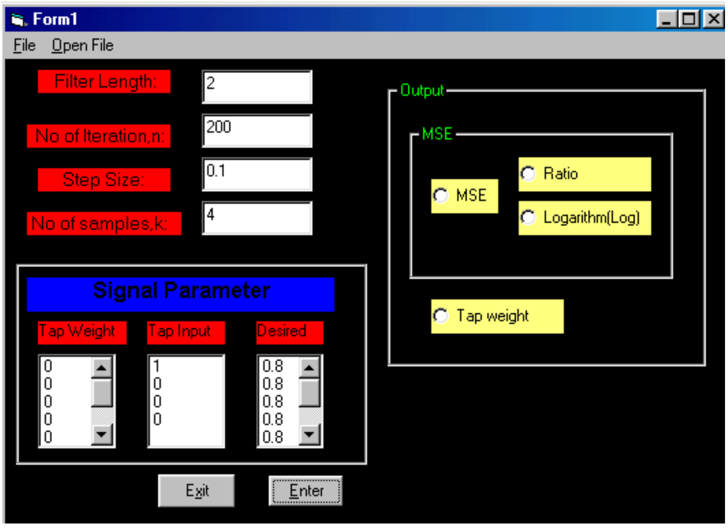
5.2 1 Load Example

In order to load an example, user can press Alt + F then follow by clicking 'Load Example' as shown in Figure 5.3(a). This action will then fill in the entire blank boxes in the software shown in Figure 5.3(b).

The signal parameter, which is loaded as an example in this program, is first being set in text files. Then from text files, it is being transfer to the corresponding text boxes and list boxes.



(a) 'File' is selected



(b) Example is loaded

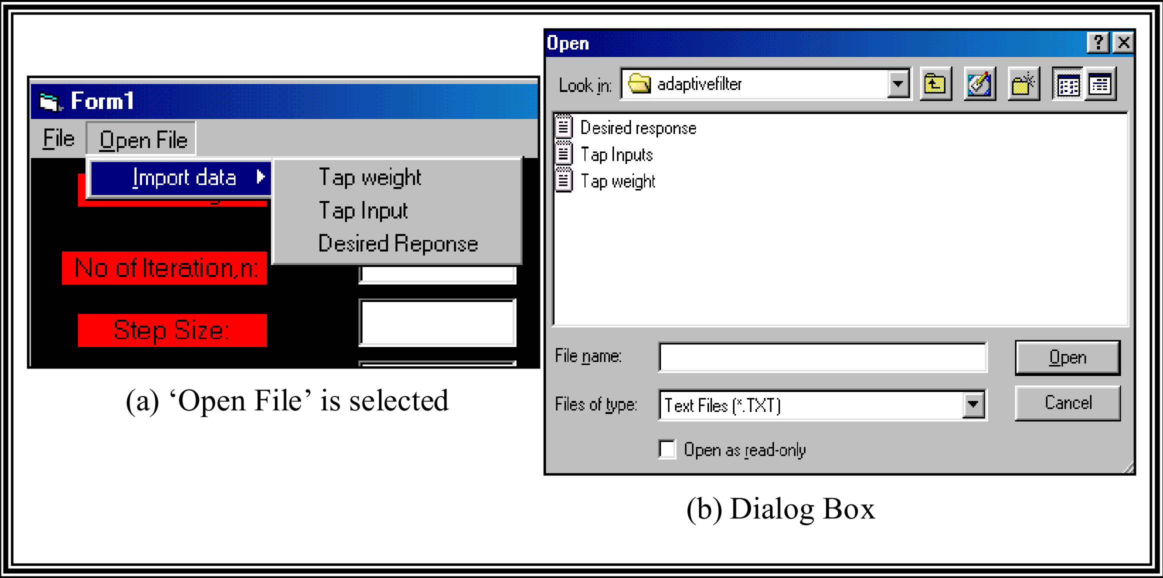
Figure 5.3 Software GUI when certain events are clicked: (a) 'File' (b) 'Load Example'

5.2.2 Assigning Signal Parameter

This process can be done by pressing Alt + O. Then user can import their data, which must be in text files (*.TXT) form. For instance, if user would like to apply value for tap weight then he has to click on 'Tap weight'. Then Dialog box shown in Figure 5.4 (b) will pop up, user just need to select which text file that contain information of tap weight. After selecting the text file, the value of tap weight will be assigned to correspond list box.

The whole process can be summarized as follow:

Click 'Open File' or press Alt + O
Click on the destination that the imported data will be located
Select the path which data is imported from
Finally, the imported data will be assigned to the correspond location



(a) 'Open File' is selected

(b) Dialog Box

Figure 5.4

5.2.3 Clear

For user to clear all the parameter, user can press Alt + F and then click on 'Clear' as shown in Figure 5.2(a). Basically the method used here is the same as loading example, which has been discussed in section 5.2. The whole process of clearing all the value in their corresponding location can then be summarized as follow:

Click on 'File' or press Alt + F
Click on 'Clear'

5.2.4 Displaying Learning Curve

After assigning all the parameters, user can click 'Enter' in order to view the learning curve of the adaptation process. This curve as had been discussed in chapter 4, can be used to determine how well is the adaptation, convergence rate, stability, etc.

The lerning curves for MSE performance can be plotted either in ratio or logarithm form. User can select whetehe they want to view MSE performance or tap weight performace of LMS algorithm by selecting the option button on the right hand site of the software (refer to Figure 5.1).

From this graph, user can click on the command buttons, which are located at the right hand side of the graph as shown in Figure 5.5. These buttons will act differently if user clicks on them. For the button named 'Close', it will close the entire window (form) in Figure 5.4. While the button named 'Refresh' is to refresh the graph.

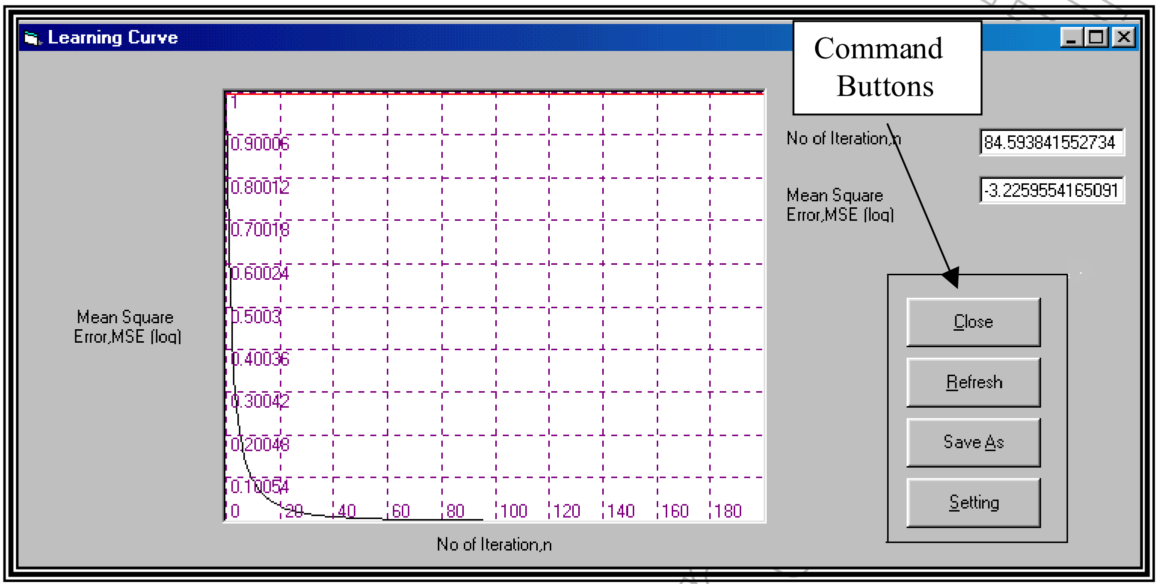


Figure 5.5 Window displaying Learning Curve

When user click on the button named ‘Saved As’ then a dialog box shown in Figure 5.6 will pop. Here user can save the graph as bitmap (*.bmp) file for reference purposes.

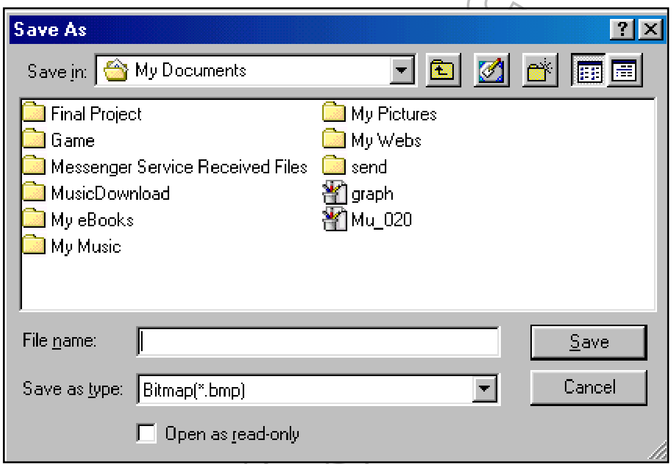


Figure 5.6 Dialog Box for saving graph

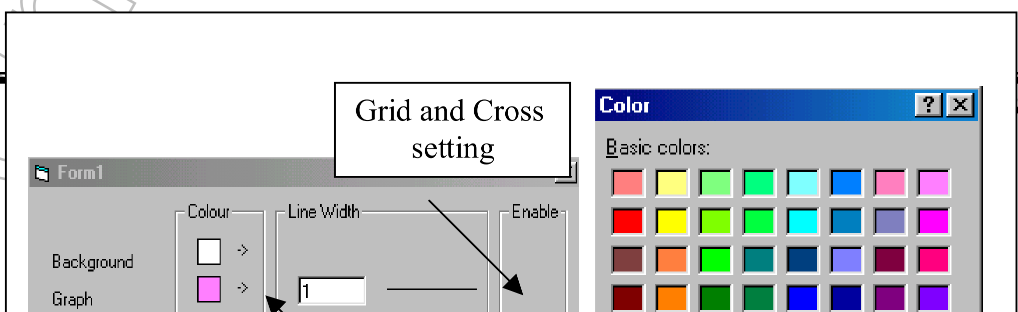


Figure 5.7 Settings (a) Form for sttings (b) Form for color settings

The command button 'Settings' is used to perform settings to the apperance of the graph. User can set whether they want the learning curve to be plotted in a graph with grid or without grid b clicking. User can even choose color for the graph background, grid and etc. The window for the setting form is shown in Figure 5.7(a). When user click on the color settings, the form shown in Figure 5.7 (b) will be displayed.

Chapter 6

Conclusions

The literature survey and research carried out in this project primarily focuses on understanding the fundamentals and characteristics of the adaptive algorithm. By having this information, it is then being implemented as a software tools to enable user to determine the characteristic and performance of adaptive filter algorithm. This chapter summarizes the research work that had been carried out in this project. Besides that it also include the summaries the project report specifying the aims and objectives achieved in this project research and some pointers to future development of this project work.

6.1 Project Achievements

The main purpose of this project is to study the fundamental concept of adaptive filtering and then implement a software tools based on the concept. The aim of this project is to create a software tools that should cover two adaptive algorithms, which is Least Mean Square (LMS) and Recursive Least Square (RLS) algorithm. With this software the performance of both algorithm can be compared and the characteristic of both algorithms also can be determined.

The first stage to develop this project is through literature search where the implementation and theoretical of adaptive filter are studied. From this literature search, the concept of adaptive filtering is obtained thus enabling the project to go one more step further. After understanding the concept, implementation of theoretical studies is being implemented. Designing the software using Visual Basic based on the theoretical concept and designing technique. After completing programming this software, testing have to be carried out. For testing part, the computation of adaptive filtering is tested based on the theoretical concept.

In this project LMS adaptive algorithm is succesfully being implemented in the software but RLS adaptive algorithm is not. The LMS algorithm property and performance is being genearlised where it had been discussed in Chapter 4. From this project, it shows that the step size and filter length of LMS algorithm plays an important role for performance measerement of LMS adaptive system. The larger the step size and filter length, the faster convergence time is obtained but this will also lead to other disadvantaged to the system such as stablity will be affected. Eventhough RLS algoritm is not succesfully being implemented into the software but the concept of RLS has been studied.

There are a lot of reason which lead to the failure of implementing RLS algorithm into the software. One of the main reason is because RLS algorithm is much more complex than LMS algorithm. Besides that time comsumption for this project also contribute to

the failure. Other than that, Visual Basic language sometimes cannot support a large computational. This is the draw back of using this programming language eventhough it has a very interesting user interface environment.

Basically this project is a very interesting project and can be used as a learning tool for student to get familiar with adaptive filter algorithm.

6.2 Future Works

The choice of adaptive algorithm of adaptive filtering system is very important. For adaptive filtering system, there are several adaptive algorithm such as Least Mean Square(LMS), Recursive Least Square (RLS), Normalized LMS (NLMS), etc. As in this software only LMS algorithm is successfully implemented. Thus one can upgrade this software into more efficient software by providing various choice of adaptive filtering algorithms.

Besides that, this software can also be implementd into different adaptive filtering configurations. In real world the structure of all this configurations are widely used. So if one can come out with a software like that it will really mean a lot to the Digital Signal Processing (DSP) world.

This software can also be implemented into DSP processor (ADSP-21065L processor). This processor comes with all software needed to develop sophisticated, high-performance DSP application.

Appendix A: Program Code of Adaptive Filter Implementation

```
Option Explicit

Dim w_arr(1000) As Double
Dim y_arr(1000) As Double
Dim x_arr(1000) As Double
Dim d_arr(1000) As Double
Dim e_arr(1000) As Double
Dim f_arr(1000) As Double
Dim m As Double, n As Double, z As Double, counter As Double

Private Sub clear_Click()
   Text1.Text = ""
   Text3.Text = ""
   List1.clear
   List2.clear
   List3.clear
   Text4.Text = ""

   form_graph.picture_gph.Cls
End Sub

Private Sub Command1_Click()
   Dim check As Double
   Dim Dummy As Double
   Dim arr(1000) As Double, new_y(1000) As Double, d_arr(1000) As Double
   Dim x As Double, t As Double
   Dim e_total(1000) As Double, MSE(1000) As Double
   Dim l As Double


   '****************LMS Implementation************************

   check = False
   z = 0
   e_total(z) = 0
   form_graph.gph_data = 0
   form_graph.list_x.clear
   form_graph.list_y.clear
   Do Until check = True
      For n = 0 To (Text1.Text - 1)
         y_arr(n) = 0
         d_arr(n) = 0
         l = 0
         For m = 0 To (Text4.Text - 1)
            Dummy = n - m
            If Not (Dummy >= 0 And Dummy < Val(Text4.Text)) Then
               Do Until (Dummy > 0 And Dummy < Val(Text4.Text))
                  If Dummy >= Val(Text4.Text) Then
                     Dummy = Dummy - Val(Text4.Text)
                  ElseIf Dummy < 0 Then
                     Dummy = Dummy + (Text4.Text)
                  End If
               Loop
            End If

            y_arr(n) = Format((List1.List(n) * List2.List(Dummy)) + y_arr(n), "0.####") 'Compute filter output
            l = l + 1

            d_arr(n) = Format(List3.List(n) * List2.List(Dummy) + d_arr(n), "0.####")
```

```
    'new_y(n) = y_arr(n)


   Next
      e_arr(n) = Format(d_arr(n) - y_arr(n), "0.####") 'Compute error

      e_total(z) = Format(e_total(z) + e_arr(n) ^ 2, "0.####")
     'MsgBox "", , e_total(z)
     'If e_total(z) = 0 Then check = True
     If z = Text2.Text Then check = True
    Next
   MSE(z) = Format((e_total(z)) / Text1.Text, "0.####")

   'add value to graph
   If Option3.Value = True Then
   form_graph.list_x.AddItem z
   form_graph.list_y.AddItem MSE(z)
   form_graph.gph_data = form_graph.gph_data + 1
   form_graph.label_x.Caption = "No of Iteration,n"
   form_graph.label_title_x.Caption = "No of Iteration,n"
   End If

   'modification to list1
   f_arr(z) = Text3.Text * e_total(z)    'Compute factor
'       MsgBox " ", , f_arr(z)

   For n = 0 To (Text1.Text - 1)
     t = 0
     For m = 0 To (Text4.Text - 1)
        Dummy = n - m
        If Not (Dummy >= 0 And Dummy < Val(Text4.Text)) Then
           Do Until (Dummy >= 0 And Dummy < Val(Text4.Text))
              If Dummy >= Val(Text4.Text) Then
                 Dummy = Dummy - Val(Text4.Text)
              ElseIf Dummy < 0 Then
                 Dummy = Dummy + (Text4.Text)
              End If
           Loop
        End If
     List1.List(n) = List1.List(n) + (f_arr(z) * List2.List(Dummy))
     t = t + 1
     'MsgBox "", , List1.List(n)
    arr(n) = List1.List(n)
    List1.List(n) = arr(n)


      Next
   Next
    If Option4.Value = True Then
   form_graph.list_x.AddItem z
   form_graph.list_y.AddItem List1.List(0)
   form_graph.gph_data = form_graph.gph_data + 1
   form_graph.label_x.Caption = "No of Iteration,n"
   form_graph.label_title_x.Caption = "No of Iteration,n"
   End If
   z = z + 1

 Loop

  'load graph

  form_graph.Visible = True
  If Option1.Value = True And Option3.Value = True Then
     form_graph.label_title_y.Caption = "Mean Square Error,MSE "
     form_graph.label_y.Caption = "Mean Square Error,MSE"
     form_graph.gph_log = False
     form_graph.func_gph_setting
     form_graph.func_gph_plot
```

```
        form_graph.Caption = "Learning Curve"
    ElseIf Option2.Value = True And Option3.Value = True Then


    form_graph.label_title_y.Caption = "Mean Square Error,MSE (log)"
        form_graph.label_y.Caption = "Mean Square Error,MSE (log)"
        form_graph.gph_log = True
        form_graph.func_gph_setting
        form_graph.func_gph_plot
        form_graph.Caption = "Learning Curve"
    ElseIf Option4.Value = True Then
        form_graph.label_title_y.Caption = "Tap Weight"
        form_graph.label_y.Caption = "Tap Weight"
        form_graph.gph_log = False
        form_graph.func_gph_setting
        form_graph.func_gph_plot
        form_graph.Caption = "Learning Curve"
    End If


End Sub

Private Sub Command2_Click()
End
End Sub


Private Sub Desired_Click()
Dim temp As String
CommonDialog1.Filter = "Text Files (*.TXT)|*.TXT|All Files (*.*)|*.*"
CommonDialog1.ShowOpen
'RichTextBox1.LoadFile (CommonDialog1.FileName)
'List1.Print .LoadFile(CommonDialog1.FileName)
'RichTextBox1.Text = w_arr(counter)
Open CommonDialog1.FileName For Input As #1
Do Until EOF(1)
Input #1, temp
List3.AddItem temp
Loop
Close #1
End Sub

Private Sub Example_Click()

Dim counter As Double

Text1.Text = 2
Text2.Text = 200
Text3.Text = 0.1
Text4.Text = 4
Open App.Path & "\Tap weight" & ".txt" For Input As #1

Do Until EOF(1)
Input #1, w_arr(counter)
List1.AddItem w_arr(counter)
counter = counter + 1
Loop
Close #1

Open App.Path & "\Tap Inputs" & ".txt" For Input As #2
Do Until EOF(2)
Input #2, x_arr(counter)
List2.AddItem x_arr(counter)
counter = counter + 1
Loop
Close #2

Open App.Path & "\Desired response" & ".txt" For Input As #3
Do Until EOF(3)
Input #3, d_arr(counter)
```

```
List3.AddItem d_arr(counter)


counter = counter + 1
Loop
Close #3


End Sub

Private Sub Form_Load()
   form_graph.Visible = False
   form_graph.list_x.clear
   form_graph.list_y.clear
End Sub

Private Sub Inout_Click()
Dim temp As String
CommonDialog1.Filter = "Text Files (*.TXT)|*.TXT|All Files (*.*)|*.*"
CommonDialog1.ShowOpen
'RichTextBox1.LoadFile (CommonDialog1.FileName)
'List1.Print .LoadFile(CommonDialog1.FileName)
'RichTextBox1.Text = w_arr(counter)
Open CommonDialog1.FileName For Input As #1
Do Until EOF(1)
Input #1, temp
List2.AddItem temp
Loop
Close #1
End Sub
Private Sub Option4_Click()
If Option4.Value = True Then
   Option1.Enabled = False
   Option2.Enabled = False
   Option3.Enabled = False
End If
End Sub

Private Sub TAP_Click()
Dim temp As String
CommonDialog1.Filter = "Text Files (*.TXT)|*.TXT|All Files (*.*)|*.*"
CommonDialog1.ShowOpen
'RichTextBox1.LoadFile (CommonDialog1.FileName)
'List1.Print .LoadFile(CommonDialog1.FileName)
'RichTextBox1.Text = w_arr(counter)
Open CommonDialog1.FileName For Input As #1
Do Until EOF(1)
Input #1, temp
List1.AddItem temp
Loop
Close #1
End Sub
```

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